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Feature-Aided Localization of Ground Vehicles Using Passive Acoustic Sensor Arrays *†

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Abstract – *Localization of moving ground targets using acoustic signals obtained by a passive sensor network, made up of acoustic sensor arrays on the ground, is a difficult problem as the signals are contaminated by wind noise and hampered by road conditions and multipath, etc., and are generally not deterministic. It becomes even more challenging when some of the vehicles are wheeled (e.g., cars) and some are tracked (e.g., tanks), and are closely spaced. In such cases the stronger acoustic signals from the tracked vehicles can mask those from the wheeled vehicles, leading to poor detection of such targets. A novel detection scheme is presented, according to which the direction of arrival (DoA) angle estimates of emitters are obtained by each sensor array using real data. The full position estimates of targets, obtained following the association of the DoA angle estimates of the* same target *from at least three sensor arrays, are used for target tracking. However, because of the particular challenges encountered in multiple ground vehicle scenarios, this association is not always reliable and thus, target tracking using kinematic (DoA angle) measurements only is difficult and it can lead to lost tracks. In this paper we propose a new feature-aided multidimensional assignment algorithm, to augment the existing assignment algorithms which use only kinematic measurements, to improve the association performance, especially in the case of wheeled vehicles. We present a novel frequency domain feature extraction technique by implementing a statistical characterization of the features, in order to enhance the accuracy of data association. The feature and DoA angle measurements are used simultaneously, via a joint likelihood function, in a multidimensional assignment (MDA) to localize targets.*

Keywords: Multidimensional assignment (MDA), feature-aided MDA, min. variance distortionless response (MVDR).

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1 Introduction

Ground vehicle tracking using acoustic data obtained from passive sensor networks is a very challenging problem. Passive acoustic sensors are gaining in popularity because of their low cost, the ease of deployment, and the fact that they can be deployed on the ground. As passive sensors do not emit their own signals like active sensors, there is no danger of being detected. Passive acoustic sensors can be used in battlefield monitoring as well as in surveillance for civilian applications.

In single target scenarios with active sensors, kinematic measurements (such as range, bearing, etc.) can be obtained, which can be used to estimate the trajectory of targets [2]. When a network of passive sensors is used, however, the range of a target can be obtained only after associating the direction of arrival (DoA or line of sight — LoS) angle estimates obtained by ***at least*** three sensors. However, "ghosting" can occur, especially in the case of road convoys [1]. Data association is difficult when the targets stay close together over an extended period of time (as acoustic signals from some targets can fade and then re-appear or can be masked by stronger signals from other targets), because one has to associate the DoA estimates from the **same target** to obtain its position. Tracking using DoA angle measurements can be done using various classification techniques [3, 5], if the identities of signal sources (targets) are known. However, this is an unreasonable assumption in multiple ground target acoustic sensor network scenarios, due to the various challenges discussed earlier. Feature-aided tracking (FAT) techniques are a new and rapidly developing research area, as they exploit certain properties of the signals, called features, in addition to the kinematic (DoA) measurements, to alleviate the difficulties encountered in conventional target tracking with kinematic measurements only.

Many of the algorithms in the literature assume the presence of a single target [5, 6] and use statistical parameters, namely the mean and variance of several har-

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14. ABSTRACT
Localization of moving ground targets us- ing acoustic signals obtained by a passive sensor net- work, made up of acoustic sensor arrays on the ground is a difficult problem as the signals are contaminated by wind noise and hampered by road conditions and multipath, etc., and are generally not deterministic. It becomes even more challenging when some of the ve- hicles are wheeled (e.g., cars) and some are tracked (e.g., tanks), and are closely spaced. In such cases the stronger acoustic signals from the tracked vehicles can mask those from the wheeled vehicles, leading to poor detection of such targets. A novel detection scheme is presented, according to which the direction of arrival (DoA) angle estimates of emitters are obtained by each sensor array using real data. The full position esti- mates of targets, obtained following the association of the DoA angle estimates of the same target from at least three sensor arrays, are used for target tracking. However, because of the particular challenges encoun- tered in multiple ground vehicle scenarios, this associ- ation is not always reliable and thus, target tracking using kinematic (DoA angle) measurements only is dif- ficult and it can lead to lost tracks. In this paper we propose a new feature-aided multidimensional assign- ment algorithm, to augment the existing assignment al- gorithms which use only kinematic measurements, to improve the association performance, especially in the case of wheeled vehicles. We present a novel frequency domain feature extraction technique by implementing a statistical characterization of the features, in order to enhance the accuracy of data association. The feature and DoA angle measurements are used simultaneously via a joint likelihood function, in a multidimensional assignment (MDA) to localize targets.

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monics of the fundamental engine firing rate of each target for identification and classification. When multiple targets are present within the surveillance region of acoustic sensor arrays, the measurements no longer exhibit the same statistics as they did for the individual targets. As a result, separate algorithms have to be developed for localizing ground vehicles in a convoy. Feature-aided data association techniques employ a ***feature-augmented*** measurement set, as compared to just kinematic measurements. Possible features could be the acoustic signature of targets from the power spectral density (PSD) of the acoustic signals. They can be used to augment the kinematic measurements obtained by each sensor to form an augmented measurement set. The major challenge is the development of reliable models to extract and characterize features. Section 2 describes the generation of the PSD of the signals received by the passive sensors using the minimum variance distortionless response (MVDR) technique [9], and the detection of DoAs of signals using the shape of the PSD. Section 3 describes a novel algorithm used to extract features from the PSD and their statistical characterization. Section 4 introduces and describes the target localization problem, i.e., estimation of full position (composite measurements) from DoA angles augmented by features. The composite measurements can be assigned to tracks using a dynamic assignment algorithm. Section 5 describes the real scenario and Section 6 provides the target localization performance comparison results between the conventional cost and feature-augmented cost based multidimensional assignment algorithms.

2 DoA Detection via Second-Order Derivative Based Thresholding

Circular sensor arrays made up of M microphones arranged equi-distantly, are employed in a passive sensor network on the ground to listen to a convoy of vehicles. Assuming that the convoy is at a sufficiently large distance from the sensor array, so that the received signals from the targets can be approximated by a planar wavefront, various wideband beamforming algorithms described in [9] can be used to detect signal sources and estimate their LoS angles with respect to the known sensor array position.

At each sampling time, an FFT is performed on the raw acoustic data from each microphone in an array, and a discrete frequency range from f_1 to f_{n_b} with bin intervals of 1 Hz is chosen for processing, where n_b is the number of bins. The frequency bins are chosen to conform to the typical frequencies of the acoustic signals emitted by engines and other moving vehicle parts. As a result we have a wide-band processing algorithm that uses data from n_b frequency bins. We denote the FFT data used for processing at each sample by $X(m, f_b)$, where $m \in \{1, ..., M\}$ represents each microphone and $f_b \in \{f_1, ..., f_{n_b}\}$ indicates the frequency bins. The MVDR algorithm provides, for each sensor array, an estimate of the power spectral density of the acoustic signals

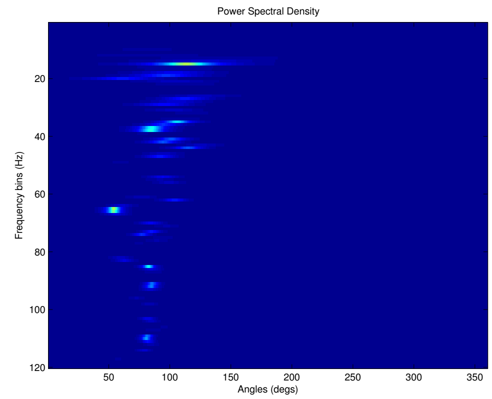


Figure 1: Power spectral density as a function of LoS angles and frequency bins obtained from the MVDR algorithm for one sensor array.

$$\hat{P}(\theta_d, f_b) = \frac{1}{\underline{a}(f_b)'\hat{R}(f_b)^{-1}\underline{a}(f_b)}$$
$$\theta_d \in \{\theta_1, ..., \theta_D\} \text{ and } f_b \in \{f_1, ..., f_{n_b}\} \tag{1}$$

and

$$\underline{a}(f_b) = \{X\}'_{f_b} V \tag{2}$$

with $\{X\}_{f_b}$ denoting the column of the matrix X corresponding to f_b, V denoting the steering matrix [9], and

$$\hat{R}(f_b) = \frac{1}{M} \sum_{m=1}^{M} X(m, f_b)^* X(m, f_b) \tag{3}$$

The DoA angles of the acoustic signals are estimated by detecting peaks in the spectrum, illustrated in Figure 1. Peak detection can be performed by applying a thresholding algorithm, using the average of the estimated power spectrum in (1) over all the frequency bins corresponding to an LoS direction θ,

$$\hat{P}(\theta) = \frac{1}{n_b} \sum_{b=1}^{n_b} \hat{P}(\theta, f_b) \tag{4}$$

For each sensor array s, $i_s(k)$ DoA angle estimates are obtained at time k.[1]

The thresholding algorithm used in the present work to detect DoAs from acoustic signals received by a sensor array is described next. Figure 1 shows an example of the estimated PSD at a particular scan for a sensor array. DoAs are detected at each scan, using a thresholding algorithm applied to the PSD of the acoustic

[1]The time index k is omitted in the future for simplicity.

signals received by each sensor array. At each angle θ in the steering vector (see Ch.2, [9]), the PSD as a function of the angle can be obtained by averaging over all the frequency bins (it is denoted by $\hat{P}(\theta)$ in (4)), and is illustrated in Figure 2(a). The first derivative of the average estimated power, $\frac{d}{d\theta}\hat{P}(\theta)$, for a particular angle θ_d (where $d \in \{1, ..., n_s\}$, and s and k are the array and scan indices, respectively) is shown in Figure 2(b). A DoA detection is made at angle θ_d if a positive peak is detected at θ_d in $-\frac{d^2}{d\theta^2}\hat{P}(\theta)$, shown in Figure 2(c). In the example shown in the figure, the DoA angles detected are 85 °, 57 ° and 102 °, arranged in decreasing order of their corresponding amplitudes.

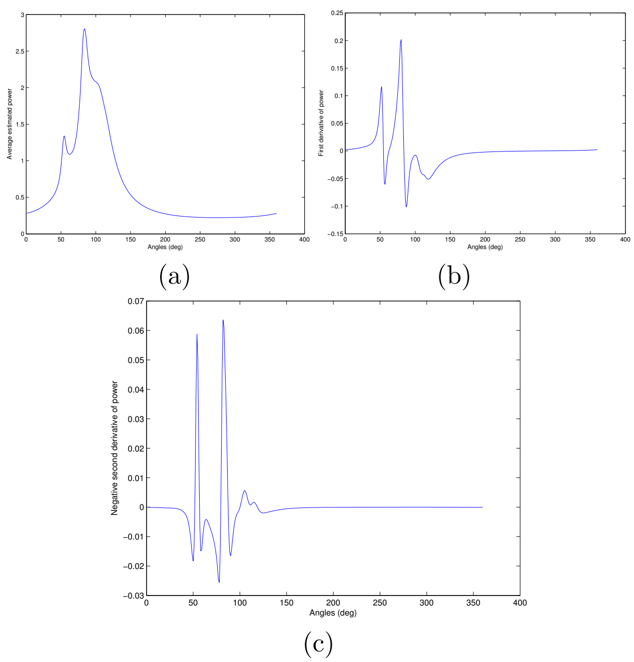


Figure 2: The thresholding used to detect DoAs from a particular sensor array at a certain scan: (a) average power spectrum as a function of angles only, (b) the first derivative of the function in (a), and (c) the negative of the second derivative of the function in (a).

Figure 3 shows the DoA angle estimates obtained by the sensor array from Figure 1. In a typical ground vehicle tracking scenario where the targets are moving in a convoy on road or off-road conditions, there are a variety of extraneous factors which affect the acoustic signal, such as road conditions, sound generated by moving parts, wind, etc. This results in numerous false alarms, i.e., power detections in frequency-angle bins not directly due to the engine or moving parts of the targets. There are also missing DoA angle estimates (missed detections) due to signal attenuation or the possible masking of signals from wheeled vehicles by those from the tracked vehicles, especially when the targets are closely spaced in a convoy. As a result, the quality of the data association is low if just the DoA angle estimates are used as measurements. Therefore, the

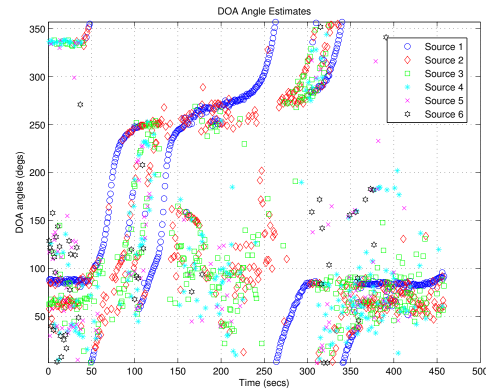


Figure 3: DoA angle estimates for one sensor array.

power spectrum will be exploited to generate features which could enhance the accuracy of data association. Motivated by this, a new feature extraction procedure is described in the next section.

3 Feature Extraction

In most feature-aided tracking applications the amplitude of the PSD peaks are used as features; however, due to signal attenuation and masking in the case of multiple vehicle road convoys, they are not reliable as features. The location and the spread of the peaks carry more useful information about the signal source, compared to the amplitude, because they are not as affected by signal attenuation. In this paper we propose a statistical modeling of the distribution of the power in the frequency bins at each detected DoA angle and use a Gaussian mixture model (GMM) to extract feature *vectors* instead of just scalar features. This method enables the use of the location and the sharpness of the peaks in the power spectrum as features.

The MVDR algorithm obtains an estimate of the power spectrum $\hat{P}(\theta_d, f_b)$ as a function of both frequency bins (f_b) and LoS azimuth angles (θ_d), as shown in (1). For each sensor s, the power spectrum along each DoA angle θ_{si_s} (where $s \in \{1, ..., S\}$ and $i_s \in \{1, ..., n_s\}$), $\hat{P}(\theta_{si_s})$, is used to declare detections in certain directions and to extract features corresponding to each detected angle at scan k.

3.1 Fitting of a Gaussian Mixture Model (GMM)

The observed data $d(x)$ (the estimated power spectrum in a particular DoA direction x) is modeled as

$$d(x) = y(x; \beta) + \epsilon(x) \tag{5}$$

where $y(x; \beta)$ is the fitted parametric model, β is the parameter vector and $\epsilon(x)$ is the fitting error. The objective is to estimate the parameters of the model such that the error (noise) is minimized in a statistical sense.

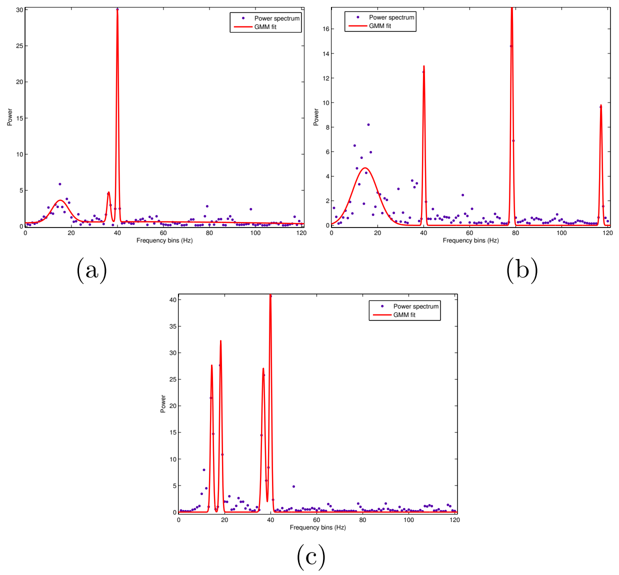


Figure 4: Gaussian mixture model fitting to extract features: (a) feature data from sensor array 1 (DoA angle θ_1, peak locations: [40,15,36,49]), (b) feature data from array 2 (DoA angle θ_2, peak locations: [78,40,117,15]) and (c) feature data from array 3 (DoA angle θ_3, peak locations: [40,18,37,14]).

The nonlinear least squares (NLLS) method is used to estimate the parameters of a nonlinear model — a GMM — used to fit the data. Gaussian mixture modeling is useful for peak finding applications. This model is given by

$$y(x;\beta) = \sum_{l=1}^{n} \alpha^l e^{-\frac{1}{2}\left(\frac{x-\mu^l}{\sigma^l}\right)^2} \tag{6}$$

where $\beta = [(\alpha^1, \mu^1, \sigma^1), ..., (\alpha^n, \mu^n, \sigma^n)]'$ is the parameter vector of the GMM such that α^l is the weight (amplitude), μ^l is the location and σ^l is the width of the peak of component l, and n is the number of components of the GMM. The NLLS method can be used to estimate the parameters of the GMM which best fit the observed data in (5). Figure 4 illustrates the GMM fitting results when applied to power spectrum data for certain DoA detections obtained by three sensor arrays at a particular time. A GMM with $n = 4$ components was used to extract the location, width and the amplitude of the peaks from the power spectrum data. A larger n was found to lead to excessive uncertainty in the feature model.

From the example illustrated in Figure 4, one can see that there are $n = 4$ frequency peaks from each of the $S = 3$ sensors, corresponding to three detected DoA angles θ_1, θ_2 and θ_3 (subscripted by the sensor index). These peak locations (arranged in decreasing order of amplitudes) form a matrix of dimension $n \times S$

$$L = \begin{pmatrix} 40 & 78 & 40 \\ 15 & 40 & 18 \\ 36 & 117 & 37 \\ 49 & 15 & 14 \end{pmatrix} \tag{7}$$

The peak location matrix given in (7) illustrates that, for the three sensor arrays in Figure 4, the peak locations are not necessarily matched across the S sensors, i.e., a peak location is not necessarily grouped with other peak locations in the $S-1$ lists (columns), in its immediate neighborhood. For example, in (7), the first row is [40 78 40]. The location of the peak in the second column (at 78 Hz) is not close to the location of the peaks in the first and third columns (at 40 Hz). Hence, in order to properly group peak locations across lists (sensors), each peak location should be matched to other peak locations (in the other lists) in such a way that each matched S-tuple of peak locations consists of peak locations which are close to each other. If a peak is located in such a way that it cannot be matched to any other peaks in the remaining lists, it is matched to a dummy element which indicates a missed peak detection. This matching of peak locations, which leads to "matched" feature vectors, is described next.

3.2 Matching the Location of Peaks via Assignment

The peak location vectors, estimated by the GMM algorithm, corresponding to each of the detected DoA angles $\theta_{1i_1}, \theta_{2i_2}, ..., \theta_{Si_S}$ are

$$\begin{aligned} \Phi^p_{1i_1,\ldots Si_S} &= [\phi^p_{1i_1}, \phi^p_{2i_2}, ..., \phi^p_{Si_S}] \\ &= \begin{pmatrix} \oslash & \oslash & \cdots & \oslash \\ \mu^1_{1i_1} & \mu^1_{2i_2} & \cdots & \mu^1_{Si_S} \\ \mu^2_{1i_1} & \mu^2_{2i_2} & \cdots & \mu^2_{Si_S} \\ \vdots & \vdots & \ddots & \vdots \\ \mu^n_{1i_1} & \mu^n_{2i_2} & \cdots & \mu^n_{Si_S} \end{pmatrix} \end{aligned} \tag{8}$$

where $\mu^l_{si_s}$ is the location of the l-th component (peak) of the GMM (6) used to fit $\hat{P}(\theta_{si_s})$ and $\oslash$ indicates the dummy element[2] that signifies missed detection of a peak. The matching of peak locations across lists is done based on the solution of an assignment problem formulated using costs attached to all the possible candidate S-tuples of peak locations in (8). Costs are derived based on a likelihood ratio for each candidate S-tuple.

[2]Indexed by zero, and shown as the top row.

3.2.1 Likelihood Function Derivations for Cost Calculation

The likelihood a candidate S-tuple of peak locations $\mu_{i_1,\ldots,i_S}$ from (8), is from the same target is

$$\Lambda(\kappa(t)) = p(\mu_{i_1,\ldots,i_S} \mid \kappa(t)) = \prod_{s=1}^{S} \left[1 - P_{D_s^f}\right]^{[1-\delta_s^f]} \cdot \left[P_{D_s^f} p\left(\mu_{si_s}^l \mid \kappa(t)\right)\right]^{\delta_s^f} \quad (9)$$

where

$$\delta_s^f = \begin{cases} 0 & \text{if } \mu_{si_s}^l = \oslash \text{ in (8)} \\ 1 & \text{otherwise} \end{cases} \quad (10)$$

is the peak location indicator, $P_{D_s^f}$ is the probability of detection of the frequency peak and $\kappa(t)$ represents the (unknown) true peak location, if the acoustic signal is from a target t. As the identity of target t is unknown, we use a generalized likelihood function $\Lambda(\hat{\kappa}(t))$ instead of the likelihood function given in (9), where the peak locations are assumed to be uncorrelated and distributed as follows

$$p\left(\mu_{si_s}^l \mid \hat{\kappa}(t)\right) = \mathcal{N}\left(\mu_{si_s}^l; \hat{\mu}^l(t), (\sigma_{si_s}^l)^2\right) \quad (11)$$

with

$$\hat{\mu}^l(t) = \frac{\sum_{s=1}^{S} \mu_{si_s}^l \delta_s^f}{\sum_{s=1}^{S} \delta_s^f} \quad (12)$$

and $\hat{\kappa}(t) = [\hat{\mu}^l(t), \ldots, \hat{\mu}^n(t)]'$, the estimated target peak location vector. The standard deviation of the peak location $\mu_{si_s}^l$ is $\sigma_{si_s}^l$, from (6). The indexing of μ and σ is augmented to indicate the peak index l, the sensor s it originated from, and the index i_s of the detection from sensor s.

The likelihood that the S-tuple of peak locations are all false alarms is

$$\Lambda(\kappa(t) = 0) = p(\mu_{i_1,\ldots,i_S} \mid \kappa(t) = 0) = \prod_{s=1}^{S} \left[\frac{1}{V_s^f}\right]^{\delta_s^f} \quad (13)$$

where V_s^f is the volume (in the frequency space) of sensor array s.

3.2.2 Cost of Matching of the Peak Locations Across S lists

The cost of matching a candidate S-tuple of peak locations $\mu_{i_1,\ldots,i_S}$ is the negative log-likelihood ratio (NLLR) obtained from the likelihood functions (9) and (13)

$$c_{i_1,\ldots,i_S}^m = \sum_{s=1}^{S} [\delta_s^f - 1] \ln[1 - P_{D_s^f}] - \delta_s^f \left[\ln\left(P_{D_s^f} V_s^f\right) + \ln p\left(\mu_{si_s}^l \mid \hat{\kappa}(t)\right)\right] \quad (14)$$

A multidimensional assignment algorithm is solved (see [1, 4, 7]), to obtain the following S-tuple of ***feature vectors corresponding to the*** S***-tuple of detected DoA angle estimates*** $\theta_{1i_1}, \theta_{2i_2}, \ldots, \theta_{Si_S}$

$$\Phi_{1i_1,\ldots Si_S} = [\phi_{1i_1}, \phi_{2i_2}, \ldots, \phi_{Si_S}] = \begin{pmatrix} \mu_{1i_1}^{j_{11}} & \mu_{2i_2}^{j_{21}} & \cdots & \mu_{Si_S}^{j_{S1}} \\ \mu_{1i_1}^{j_{12}} & \mu_{2i_2}^{j_{22}} & \cdots & \mu_{Si_S}^{j_{S2}} \\ \vdots & \vdots & \ddots & \vdots \\ \mu_{1i_1}^{j_{1n_m}} & \mu_{2i_2}^{j_{2n_m}} & \cdots & \mu_{Si_S}^{j_{Sn_m}} \end{pmatrix} \quad (15)$$

where $\mu_{si_s}^{j_{sq}} \in \{\oslash, \mu_{si_s}^l\}$ and $q = 1, \ldots, n_m$. Each element $\mu_{si_s}^l$ in the s-th list of (8) appears exactly once in the s-th column of (15), while $\oslash$ appears $n_m - n$ times in each column of (15). It has to be noted that n_m could vary with each S-tuple of DoA angle estimates being considered, while n remains the same as it is a GMM fitting design parameter and is fixed.

The illustrative example presented next corresponds to the same triplet ($S = 3$) of DoA angle estimates $\theta_1, \theta_2, \theta_3$, which gives rise to the peaks illustrated in Figure 4. The triplet of ***peak location vectors*** of length $n = 4$ are as shown in (7). The triplet of ***feature vectors***, each of length $n_m = 7$, obtained after performing the matching of peak locations as described above is

$$L^{\text{matched}} = \begin{pmatrix} 40 & 40 & 40 \\ 15 & 15 & 14 \\ 36 & \oslash & 37 \\ 49 & \oslash & \oslash \\ \oslash & 78 & \oslash \\ \oslash & 117 & \oslash \\ \oslash & \oslash & 18 \end{pmatrix} \quad (16)$$

4 Target Localization by Feature-Aided MDA

One of the most important issues in multisensor-multitarget (MSMT) tracking is data association. Recently, a class of algorithms called multidimensional assignment (MDA) algorithms (also known as S-D assignment) have been developed to solve the data association problem using an assignment approach [1, 7]. The present paper uses the MDA approach to solving the data association problem. This approach, designated as Multisensor Information Configuration III in [1], requires a **static association** of measurements to measurements, across sensor arrays at each time k, resulting in complete position estimates called "composite measurements". If the DoA angle measurements are augmented by features, the result will be feature-augmented composite measurements.

In the feature-aided MDA problem, at time k, we are given S lists of feature-augmented measurement vectors from S passive sensors gathering data in a surveillance region. The position of each sensor array $s = 1, \ldots, S$ is denoted by $\mathbf{x}_s$ (the sensor array positions are assumed to be fixed throughout the track-

ing scenario[3]). An S-tuple of DoA angle measurements $Z_{i_1,...i_S}$ can be augmented with an S-tuple of feature vectors $\Phi_{i_1,...i_S} = \{\phi_{1i_1},...,\phi_{Si_S}\}$, where each angle measurement θ_{si_s} has its own corresponding feature vector ϕ_{si_s}, to form an S-tuple of feature-augmented measurement vectors

$$Z^a_{i_1,...i_S} = [Z_{i_1,...i_S}, \Phi_{i_1,...i_S}]' \quad i_s \in \{0,1,...,n_s\} \tag{17}$$

where $i_s = 0$ represents the dummy measurement or a missed detection. Generalized likelihood ratio based costs are generated for assigning each such S-tuple.

The generalized likelihood that the S-tuple $Z^a_{i_1,...i_S}$ consists of feature-augmented measurement vectors from a target t is

$$\Lambda^G_A(t) = p\left(Z^a_{i_1,...i_S}\,|\,t\right) = p\left([Z_{i_1,...i_S}, \Phi_{i_1,...i_S}]\,|\,(\hat{\mathbf{x}}_t, \hat{\varphi}_t)\right) \tag{18}$$

where $\hat{\mathbf{x}}_t$ is the ML estimate of the position of target t and $\hat{\varphi}_t$ is the estimated feature vector of target t. Assuming that the angle measurement errors and the feature vectors are independently distributed, we have

$$\Lambda^G_A(t) = p\left(Z_{i_1,...i_S}\,|\,\hat{\mathbf{x}}_t\right) p\left(\Phi_{i_1,...i_S}\,|\,\hat{\varphi}_t\right) = \Lambda^G_K(t)\Lambda^G_\phi(t) \tag{19}$$

where $\Lambda^G_K(t)$ and $\Lambda^G_\phi(t)$ represent the kinematic and feature generalized likelihood functions, respectively.

The generalized likelihood that an S-tuple of kinematic (DoA angle) measurements $Z_{i_1,...,i_S}$ are from a target t with ML position estimate $\hat{\mathbf{x}}_t$, is given by

$$\Lambda^G_K(t) = p(Z_{i_1,...,i_S}\,|\,t) = \prod_{s=1}^{S} \Big\{ [1 - P_{D_s}]^{1-u(i_s)} \cdot [P_{D_s} p(\theta_{si_s}\,|\,\hat{\mathbf{x}}_t)]^{u(i_s)} \Big\} \tag{20}$$

where $u(i_s)$ is the DoA detection indicator function and P_{D_s} is the probability of detection of a bearing measurement, by sensor array s. Each DoA angle measurement is assumed to be normally distributed with the following pdf

$$p(\theta_{si_s}\,|\,\hat{\mathbf{x}}_t) = \mathcal{N}(\theta_{si_s}; h(\hat{\mathbf{x}}_t, \mathbf{x}_s), \sigma^2_{si_s}) \tag{21}$$

where h is the measurement function.

The generalized likelihood that an S-tuple of feature-vector measurements $\Phi_{i_1,...,i_S}$ corresponding to an S-tuple of angle measurements $Z_{i_1,...,i_S}$ are from a target t, with feature estimate $\hat{\varphi}_t$, is given by

$$\Lambda^G_\phi(t) = p\left(\phi_{1i_1}, \phi_{2i_2}, ..., \phi_{Si_S}\,|\,\hat{\varphi}_t\right) \tag{22}$$

where ϕ_{si_s} is the feature vector (15) corresponding to the DoA angle measurement θ_{si_s} from the s-th list

$$\phi_{si_s} = [\mu^1_{si_s}, \mu^2_{si_s}, ..., \mu^{n_m}_{si_s}]' \tag{23}$$

where $\mu^l_{si_s}$ ($l = 1,...,n_m$) represents either a feature (detected matched peak location) or a dummy (missed detection of the peak in list s), as described in Section 3.2.2.[4]

Assuming independence between measurement lists, (22) can be simplified to

$$\Lambda^G_\phi(t) = \prod_{s=1}^{S} \left\{p\left(\phi_{si_s}\,|\,\hat{\varphi}_t\right)\right\}^{u(i_s)} \tag{24}$$

Substituting from (23) in (24), and assuming uncorrelatedness between the components of the feature vector ϕ_{si_s}, we have

$$\Lambda^G_\phi(t) = \prod_{s=1}^{S} \left\{ \prod_{l=1}^{n_m} [1 - P_{D^l_s}]^{1-\delta_{s_l}} \left[P_{D^l_s} p\left(\mu^l_{si_s}\,|\,\hat{\varphi}_t\right)\right]^{\delta_{s_l}} \right\}^{u(i_s)} \tag{25}$$

where $P_{D^l_s}$ is the (nonunity) probability of detection of the features in list s, while δ_{s_l} is the detection indicator function for the feature $\mu^l_{si_s}$. The feature vector component $\mu^l_{si_s}$ is assumed to be distributed as follows

$$p\left(\mu^l_{si_s}\,|\,\hat{\varphi}_t\right) = \mathcal{N}\left(\mu^l_{si_s}; \hat{\mu}^l(t), (\sigma^l_{si_s})^2\right) \quad i_s \in \{1,...,n_s\} \tag{26}$$

where

$$\hat{\mu}^l(t) = \frac{\sum_{s=1}^{S} \mu^l_{si_s}\delta_{s_l}}{\sum_{s=1}^{S} \delta_{s_l}} \tag{27}$$

The standard deviation $\sigma^l_{si_s}$ of the peak location $\mu^l_{si_s}$ is obtained from the GMM fitting in (6).

The generalized likelihood that the S-tuple $Z^a_{i_1,...,i_S}$ consists of feature-augmented measurement vectors which are all spurious or are unrelated to a target t is

$$\begin{aligned}\Lambda^G_A(t=0) &= p\left(Z^a_{i_1,...,i_S}\,|\,t=0\right) \\ &= \prod_{s=1}^{S}\{p\left(\theta_{si_s}\,|\,t=0\right) p\left(\phi_{si_s}\,|\,\varphi(t)=0\right)\}^{u(i_s)} \\ &= \prod_{s=1}^{S} \Bigg\{p\left(\theta_{si_s}\,|\,t=0\right) \\ &\qquad \cdot \left[\prod_{l=1}^{n_m} p\left(\mu^l_{si_s}\,|\,\varphi(t)=0\right)\right]^{\delta_{s_l}} \Bigg\}^{u(i_s)}\end{aligned} \tag{28}$$

Assuming that the angle and feature vector element false alarm measurements are uniformly distributed, we have

$$\Lambda^G_A(t=0) = \prod_{s=1}^{S} \left\{ \frac{1}{V_s} \left[\prod_{l=1}^{n_m} \frac{1}{V^f_s}\right]^{\delta^l_s} \right\}^{u(i_s)} \tag{29}$$

[3]The approach can be easily generalized to moving sensors (see, e.g., [2]).

[4]The length of the feature vector n_m varies for each candidate S-tuple of feature-augmented measurement vectors, as explained in Section 3.2.2, additional notation is omitted for simplicity.

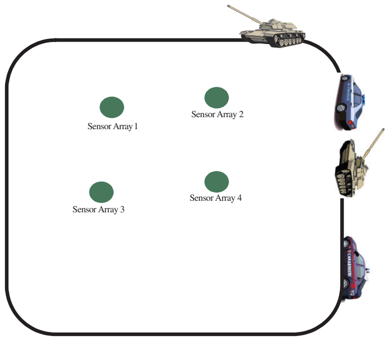


Figure 5: A passive sensor network of 4 acoustic sensor arrays listening to a convoy of 4 wheeled and tracked vehicles.

where V_s and V_s^f are the surveillance volumes in angle and frequency, respectively, of sensor array s.

The cost of assigning the S-tuple $Z^a_{i_1,\ldots,i_S}$ is given by the NLLR obtained from the generalized likelihood functions (19) and (29), and substitution from (20) and (25)

$$c_{i_1,\ldots,i_S} = -\ln \frac{\Lambda_A^G(t)}{\Lambda_A^G(t=0)} = -\ln \frac{\Lambda_K^G(t)\Lambda_\phi^G(t)}{\Lambda_A^G(t=0)} \quad (30)$$

This cost function can be simplified to the following form:

$$\begin{aligned} c_{i_1,\ldots,i_S} \;=\; & -\sum_{s=1}^{S}[1-u(i_s)]\ln(1-P_{D_s}) \\ & +u(i_s)\ln\left[P_{D_s}V_s p(\theta_{si_s}\,|\,\hat{\mathbf{x}}_t)\right] \\ & +u(i_s)\left\{\sum_{l=1}^{n_m}(1-\delta_s^l)\ln(1-P_{D_s^l}) \right. \\ & \left. +\,\delta_s^l \ln\left[P_{D_s^l}V_s^f p\left(\mu_{si_s}^l\,|\,\hat{\varphi}(t)\right)\right]\right\} \quad (31)\end{aligned}$$

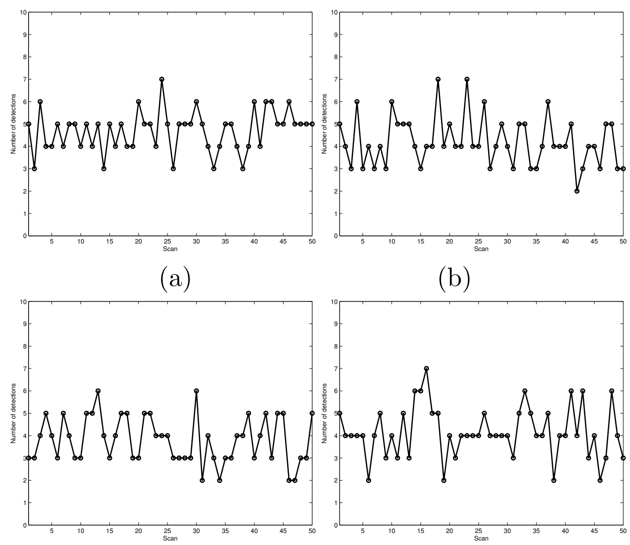
The most likely set of S-tuples such that each feature-augmented measurement vector in a list is assigned to either other measurement vectors, or declared false, with the constraint that each assigned S-tuple receives at most only one measurement vector from each list, is obtained by solving a global S-D optimization problem using the cost function (31). A Lagrangian relaxation algorithm is used to solve this problem [1, 4, 7].

5 Scenario

The algorithm developed above was exercised on real data obtained from a field experiment [5]. Four acoustic arrays were placed within a path that was traveled by multiple targets (see Figure 5). All the acoustic sensor arrays used in the experiment were circular arrays of microphones.

Each sensor array has a field of view of 360° and is made up of 7 equi-distant microphones. DoA angle measurements are estimated at each sample time (1 s), from the PSD of the acoustic signals received by each sensor array, as described in Section 2, with a measurement error standard deviation of 2°. The PSD of the acoustic signals is estimated using an MVDR beamformer, where a steering vector of length 360 (all possible angles/directions) is considered. A low-pass spectrum of 1–120 Hz, divided into bins of 1 Hz each, is used by the MVDR algorithm.

Figure 6 shows the number of DoAs detected at each scan for the four sensor arrays used in the scenario. The measurement lists in both conventional and feature-aided assignment consist of the same number of DoA detections per scan. They only differ in whether feature vectors augment (as described in Section 3) to the DoA angle measurements or not. One can observe from the figure that there are false alarms as well as missed detection in several scans, as there are four targets in this scenario and the number of detections varies from 2 to 7.



(a) (b)

(c) (d)

Figure 6: Number of DoA detections at each scan, for both conventional and feature-aided assignment: (a) from sensor array 1, (b) from array 2, (c) from array 3 and (d) from array 4.

For target localization using the conventional cost, an MDA algorithm is solved [1], with DoA measurement probability of detection $P_{D_s} = 0.9$ and sensor array surveillance region volume $V_s = 360°$. For target localization using the feature-augmented cost (31), an MDA algorithm is solved at each scan. The probability of detection of the features is assumed to be $P_{D_s^l} = 0.7$ and the surveillance volume in frequency is assumed to be $V_s^f = 120$ Hz (the width of the frequency spectrum).

6 Results

The real data based results shown in Figure 7 show the comparison between the performance of the con-

ventional cost and feature-augmented cost based target localization algorithms. The figure presents the complementary cumulative density function of the number of detected targets. The localization results obtained for 50 scans show that the feature-aided localization algorithm outperforms significantly the conventional cost based algorithm. The figure shows that the conventional cost based assignment algorithm performs poorly in detecting the full set of targets. This is because the stronger acoustic signals emitted by the tracked vehicles can mask those from the wheeled vehicles, leading to missed detection of some DoA angle measurements by one or more sensor arrays. Hence, using only kinematic measurements for static assignment leads to the missed detection of some targets.[5] Augmenting the kinematic measurements with feature measurements alleviates this problem by adding more information to the cost function, and hence, resulting in more feasible solutions to the global assignment algorithm. The feature-aided target localization algorithm in this particular example is able to localize all 4 targets, in 32 scans out 50, while the conventional algorithm manages to do the same in 7 out of 50 scans. Overall, the estimated detection probability for a target composite measurement (in the absence of ground truth, calculated as the total number of composite measurements from 50 scans knowing that there were 4 targets) is $\frac{184}{200} = 0.92$ and $\frac{136}{200} = 0.68$ for the feature-aided and conventional schemes, respectively.

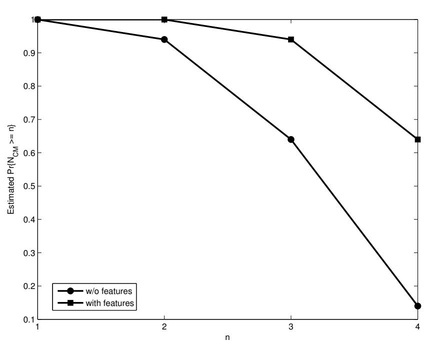


Figure 7: Comparison of the estimated probability of localizing at least n targets out of 4 for the feature-aided assignment algorithm and the conventional assignment algorithm (without features).

7 Conclusions

In this paper a data association algorithm to localize multiple ground targets using acoustic signal data obtained by a passive sensor network, has been solved using a novel feature-aided multidimensional assignment framework. A novel detection scheme has been presented to detect DoAs and a new technique has been presented to extract feature vectors, instead of features, which augment their corresponding DoA angle measurements. An MDA algorithm is solved at each scan, using feature-augmented likelihood ratio based cost functions, to obtain composite measurements which are the full position estimates of targets. It is shown using real data obtained by a passive sensor network, that the feature-aided assignment algorithm significantly outperforms its conventional kinematic counterpart in the localization of multiple targets, where some targets are tracked vehicles and the others are wheeled vehicles. Ongoing work consists of assigning the full position estimates of targets obtained by the feature-aided static assignment algorithm to tracks via a dynamic assignment algorithm.

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[5] Assigning DoA angle measurements from at least 3 lists is needed for a detection.